Noname manuscript No.
(will be inserted by the editor)

Taming financial systemic risk: models, instruments and early warning indicators.

Gabriele Tedeschi · Fabio Caccioli · Maria Cristina Recchioni

Received: date / Accepted: date

Can "It" Happen Again?

In recent decades, most advanced and developing economies have suffered — or are still suffering — from profound and repeated crises. The literature has reflected on the determinants of these perturbations by placing particular emphasis on the malfunctioning of either the real or financial sphere of the economy. The main research question has been to understand if it was the real economy that perturbed finance sectors or, alternatively, the financial/credit market that depressed real production. Whatever the direction of the causality nexus and, consequently the origin of the attack, with some studies identifying the direction from real markets to financial sectors (see Bernanke and Gertler, 1989; Greenwald and Stiglitz, 1993; Delli Gatti et al., 2012) and others reversing it (see Christiano and Ikeda, 2011; Brunnermeier et al., 2012), what is certainly undoubted is the self-reinforcing interaction between the two sectors, which translates into booms followed by busts. In light of this, part of the literature has not focused as much on the origin of crises, but rather on the mechanisms of shock propagation. In this regard many studies have shown that a combination of forces is needed to generate shock transmission. Specifically, the literature on contagion has shown that agents' interaction and the emerging network topology are key ingredients for the spread of systemic risk (see, for instance, Lux, 2016; Lux and Montagna, 2017). The interaction has in fact been recognized as generating two opposing effects: risk sharing, which decreases with connectivity and systemic risk, which in contrast, increases with linkages (see, for instance, Allen & Gale, 2000; Battiston et al., 2007, 2012a, 2012b; Grilli et al., 2014; Iori et al., 2006; Mazzarisi et al., 2020; Tedeschi et al., 2012). Many other studies have confirmed the non-linearity of this relationship. This body of work has also shown that other factors must be added to generate the catastrophic effects that characterized the 2007 financial collapse, namely the agents' heterogeneity and financial fragility (see Aymanns et al., 2016;

Gabriele Tedeschi, corresponding author
Department of Economics, Universitat Jaume I, Av. de Vicent Sos Baynat, s/n 12071 Castellon, Spain. E-mail: gabriele.tedeschi@gmail.com

Fabio Caccioli
Department of Computer Science, University College London, London, WC1E 6EA, UK Systemic Risk Centre, London School of Economics and Political Sciences, London, WC2A 2AE, UK

Maria Cristina Recchioni
Department of Economics and Social Sciences, Universitá Politecnica delle Marche, Piazzale Martelli 8, 60121 Ancona, Italy.

Bardoscia et al., 2017; Caccioli et al., 2011, 2014, 2015; Lenzu and Tedeschi, 2012). In fact, as reported by Berardi & Tedeschi (2017) "on the one hand, the possible emergence of contagion depends crucially on the degree of heterogeneity. Indeed, when the agents' balance sheets are heterogeneous, banks are not uniformly exposed to their counter-party. Therefore, if contagion is triggered by the failure of a big bank, which represents the highest source of exposure for its creditors, the situation is certainly worse than when agents are homogeneous [...]. On the other hand, the probability of default in credit markets is strictly linked to the presence of highly leveraged agents [...]. Indeed, when variations in the level of financial robustness of institutions tend to persist in time or to get amplified, financial linkages among financially fragile banks represent a propagation channel for contagion and a source of systemic risk." Interestingly enough, this second element is very close in spirit to the Minskyan financial instability hypothesis, where endogenous shifts in the degree of financial fragility of agents generate business fluctuations and, possibly, the materialization of bankruptcy cascades (see Minsky, 1964; Ferri and Minsky, 1992).

Once again the Minskyan "prophecy" has come true: it has happened.

Based on the lessons of the recent socioeconomic crisis, the aim of this special issue is to identify some mechanisms that may generate systemic risk and contagion, and possibly tools to anticipate their onset. As the reader will appreciate, the essays collected here try to address the problem of systemic risk by using different approaches. The motivation for this choice is twofold. Firstly, it has been shown that systemic risk is a highly complex phenomenon that certainly cannot be encapsulated within a single modeling approach. In fact, the main problem with the "standard" monitoring system is that it was based on the idea that crises depend on exogenous and aggregate shocks, while in reality endogenous small local shocks can also trigger large systemic effects. The multiple fuses that trigger systemic risk explain the motivation for bringing together several methodologies, each one of which is able to grasp a different angle of the problem (see also Alfarano et al., 2019; Bargigli and Tedeschi, 2013; Grilli et al., 2017). Secondly, we believe in the science of complexity, which recommends studying the economic system starting with the coevolution of its sub-systems and not breaking it down into disjointed, non-communicating sub-spheres. In sum, Mr. Trichet' s words describe our purpose well: "the key lesson we would draw from our experience is the danger of relying on a single tool, methodology or paradigm. Policy-makers need to have input from various theoretical perspectives and from a range of empirical approaches. ...we need to develop complementary tools to improve the robustness of our overall framework. ...In this context, we would very much welcome inspiration from other disciplines: physics, engineering, psychology, biology. Bringing experts from these fields together with economists and central bankers is potentially very creative and valuable. Scientists have developed sophisticated tools for analyzing complex dynamic systems in a rigorous way. These models have proved helpful in understanding many important but complex phenomena: epidemics, weather patterns, crowd psychology, magnetic fields. Such tools have been applied by market practitioners to portfolio management decisions, on occasion with some success."

Essays on Instability and Finance

From theoretical microeconomic and financial mathematical models up to network theory, experimental economic model, econometric analysis, and agent-based methodologies, we present ten different approaches capable of grasping the (in)stability of financial systems. Although very different, these papers identify some of those many sources with which contagion can start.

We now briefly describe the ten selected papers.

The first two papers by Mazzocchetti et al., 2019 and Vidal-Tomás & Alfarano, 2019 offer a new interpretation of two classics in the agent-based literature. On the one hand, Mazzocchetti et al. incorporate a securitization process and bailout mechanism for bank bankruptcies within the well-know Eurace framework. The authors show that in the medium term, an increase in banks' securitization propensity reduces the financial stability of the credit market and this negatively affects all other sectors. Most importantly, Mazzocchetti et al. introduce a composite systemic financial risk indicator. This indicator shows that actions ensuring the soundness of one institution, such as solvency, liquidity capacity, banks' leverage, etc., may not be consistent with ensuring the soundness of another. On the contrary they may even decrease the stability of the system as a whole. Indeed, local shocks can have systemic repercussions and the requirement to have sounder individuals can lead to the counter-intuitive effect of making the entire system more fragile. On the other hand, Vidal-Tomás & Alfarano propose a new application of Kirman's ant colony model (see Kirman, 1991, 1993). Specifically, the authors link the Kirman seminal switching model with an investor-sentiment index and show how market dynamics can be captured by the collective behavior of traders following waves of optimism and pessimism. Moreover, Vidal-Tomás & Alfarano introduce an early warning indicator based on a combination of the ants model and the sentiment index. This indicator identifies systemic risk through the switching between the waves of optimism and pessimism characterizing stock time series.

Before presenting the other manuscripts in our special issue, we would like to highlight another important contribution contained in the work of Vidal-Tomás & Alfarano, that is, a well-calibrated agent-based model is an effective descriptive and predictive tool. Although there are many obstacles to calibrating agent-based models (the high number of parameters, among others), what clearly emerges is the great descriptive and predictive potential of these models once well estimated (see, also, Alfarano et al., 2005, 2006 and Recchioni et al., 2015).

Similar to the work by Mazzocchetti et al., Ciola, 2019 identifies banks' behavior as the source of systemic risk (see Tedeschi et al., 2019, for similar results). By implementing a theoretical microeconomic model, the author shows that an increase in the bargaining power of banks can decrease the entrance of new financial institutions in the credit market, thus negatively affecting the growth rate and the volatility of aggregate production. Specifically, Ciola shows that barriers to entry into the credit market during periods of economic expansion generate gridlock effects and credit crunch phenomena.

The work by Colasante et al., 2019 is very different in spirit to all previous papers on systemic risk. By using experimental economics, the authors analyze the emergence of systemic risk in an alternative context, that is, the creation (destruction) of a public good. By implementing a public-good experiment with a voluntary contribution mechanism and uncertain individual returns, Colasante et al. study the effect of uncertainty on the appearance agents who might behave as free-riders. The authors show that a high level of uncertainty can lead to significantly lower individual contributions and, consequently, give rise to the tragedy of the commons. As is well known, in fact, this phenomenon belongs to the broad class of coordination failures which fall under the many possible explanations for the emergence of credit friction (see, Aikman et al., 2015; Bassetto et al., 2015; Rajan, 1994).

The next three selected works analyze systemic risk starting from the study of the interaction. Whichever way this is modeled, either via **i)** network theory tools, or **ii)** balance sheet interconnectedness among agents, the interaction among market-participants represents the channel to propagate/reduce financial friction. Following the network-theory approach, the papers by De Masi and Ricchiuti, 2019 and Clemente et al., 2019 empirically analyze the impact that recognized episodes of systemic risk, such as the Lehman failure and the sovereign debt crisis, have on the network topology of the European Foreign Direct Investment (FDI), in the first paper, and the European banking system, in the second. Although the systems are very different, both papers use a common technique. They study the time evolution of various network measures and correlate them with some important episodes of contagion characterizing the period investigated. Both studies show how interconnections change over time and display abrupt changes during episodes of contagion. Moreover, both studies highlight how these abrupt changes can predict systemic risk. On the other hand, the paper by Fatone and Mariani, 2019 describes interaction via banks' balance sheet interdependence. The authors model the time evolution of banks' assets/liabilities via a system of interacting stochastic differential equations. By exogenously shocking banks' equity, the authors study the evolution of systemic risk and implement monetary policy countermeasures to contain the diffusion of bankruptcy cascades. Specifically, these countermeasures are obtained by solving an optimal control problem for the pseudo mean field approximation of model.

Still using a quantitative approach, the paper by Mancino and Sanfelici, 2019 develops an indicator of market instability called the *price-volatility feedback rate*. It combines the volatility, leverage, and leverage/price covariance in a non-linear way. The price-volatility feedback rate is designed to describe the ability of the market to absorb or amplify any given market perturbation. Mancino and Sanfelici numerically investigate the properties of their proposed financial instability estimator using both synthetic and real data (i.e., tick-by-tick data from S&P 500 index futures). Finally, the authors obtain an analytical formula for their estimator when the asset price dynamics follows the CEV (constant elasticity variance) model. In the most general case, that is, when the model of the asset price dynamics is not specified, the indicator is estimated through the Fourier transform method. A new consistency theorem for the estimator of each component of the proposed indicator is also proved.

Simulation techniques for modeling portfolio trading strategies have proved to be very effective in understanding the onset of systemic risk. Following this line of research, the paper by Sakurai and Kurosaki, 2019 investigates the emergence of systemic risk in over-the-counter (OTC) derivatives markets. The modeled banks optimally hedge credit valuation adjustment (CVA) by trading a credit default swap (CDS). By modeling counter-party risk, the authors capture the well-known adverse effect, the "CDS-CVA feedback loop"[1] and show how this phenomenon emerges in illiquid markets and generates strong volatility.

The problem of markets' illiquidity in generating systemic risk via credit crunch phenomena is also the key topic of the last selected paper by Kapar et al., 2019. This paper performs an empirical analysis of the European electronic interbank market (e-MID interbank market) in the period 2006–2009. The authors explain how changes in the lending/borrowing strategies are due to the liquidity turmoil characterizing the period investigated. More in detail, Kapar et al. show that liquidity turmoil is one of the crucial determinants in lending/borrowing spread. Specifically, their results show that the spread is particularly high during the morning trading session and, consequently, the borrowing (lending) positions are more unfavorable (favorable) during this time of day. This suggests the possibility of opportunistic behavior for banks with a liquidity surplus, thereby lending in the morning and borrowing in the afternoon. As the authors point out, this trading strategy is particularly exploited by big financial institutions which can therefore find better credit conditions. This finding leads the authors to an obvious conclusion: the largest banks do not survive due to the well-known "too-big-to-fail" phenomenon, but rather due to their ability to adopt opportunistic strategies.

Concluding remarks

As stated by Recchioni and Tedeschi (2017): "The financial and economic crisis that started in 2007 is a clear symbol of the materialization and propagation of systemic risk. Systemic risk and the potential ensuing contagion refer to a situation whereby the instability in a given country, market or institution is transmitted to one or more countries, markets or institutions. On the one hand, the strong interaction at the micro- and meso-level generated the well-known knock-on effect, which culminated in the demise of Lehman Brothers. On the other hand, the same interdependence at the macro level has played a key role in exacerbating the sovereign debt problems in the Euro zone. As a consequence, macro and financial economists and market participants have all attempted to build reliable models to describe and anticipate systemic risk. Although the resulting models are very different in form and fit, they all incorporate the interactions as a key element in generating crisis and contagion." The papers collected in this special issue have tried to move precisely in this direction. These essays are the voice of different methodological approaches, each of which has highlighted some mechanism by which contagious can emerge and spread. Moreover all of these works have clearly shown that systemic risk is a complex phenomenon generated by a plurality of variables interacting in a non-linear way.

Acknowledgements Gabriele Tedeschi is grateful for the financial support by the Universitat Jaume I (grant UJI-B2018-77) and the Spanish Ministerio de Ciencia, Innovacion y Universidades (grant $RTI2018-096927-B-I00$).

[1] For a definition of this phenomenon, we refer the reader to Brunnermeier et al., 2013: "When a bank enters into any contract with a counterparty, it becomes exposed to counterparty credit risk arising from the failure of the latter to perform on the contract. The Credit Valuation Adjustment (CVA) is the market value of this counterparty credit risk. Banks currently calculate and manage CVA risks according to different business models and subject to different accounting regimes. [...] Corporate and sovereign counterparties for instance typically cannot or will not post collateral. In such a case, the only way for these banks to reduce the CVA capital charge on trades with those counterparties is to buy CDS protection. However, since the CVA charge is partly based on the volatility of CDS spreads, a surge in demand for protection may drive their capital charge up, leading banks to buy more CDS protection, and so on and so forth."

References

1. Aikman D., Haldane A.G., and Nelson B.D., (2015). Curbing the credit cycle. The Economic Journal, 125 (585):1072-1109.
2. Alfarano, S., Lux, T., Wagner, F., (2005). Estimation of Agent-Based Models: The Case of an Asymmetric Herding Model. Computational Economics, 26 (1), pp 19-49.
3. Alfarano, S., Lux, T., Wagner, F., (2006). Estimation of a simple agent-based model of financial markets: An application to australian stock and foreign exchange data. Physica A, 370 (1), 38-42.
4. Alfarano, S., Camacho, E., Tedeschi, G., (2019). Alternative approaches for the reformulation of economics. Journal of Economic Interaction and Coordination 14 (1), 1-6.
5. Allen, F., & Gale, D. (2000). Bubbles and crises. The Economic Journal, 110(460), 236-255.
6. Aymanns, C., Caccioli, F., Farmer, JD., Tan, VWC., (2016). Taming the Basel leverage cycle. Journal of financial stability 27, 263-277.
7. Bardoscia, M., Battiston, S., Caccioli, F., Caldarelli, G., (2017). Pathways towards instability in financial networks. Nature Communications 8, 14416.
8. Bargigli, L. & Tedeschi, G., (2013). Major trends in agent-based economics. J Econ Interact Coord 8:211. https://doi.org/10.1007/s11403-012-0105-6.
9. Bassetto M., Cagetti M., and De Nardi M., (2015). Credit crunches and credit allocation in a model of entrepreneurship. Review of Economic Dynamic, 18(1): 53-76.
10. Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. (2007). Credit chains and bankruptcy propagation in production networks. Journal of Economic Dynamics and Control, 31(6), 2061-2084.
11. Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. (2012). Default cascades: When does risk diversification increase stability? Journal of Financial Stability, 8(3), 138-149.
12. Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. Journal of Economic Dynamics and Control, 36(8), 1121-1141.
13. Berardi, S., Tedeschi, G., (2017). From banks' strategies to financial (in) stability. International Review of Economics & Finance 47, 255-272.
14. Bernanke B. and Gertler M., (1989) Agency costs, net worth, and business fluctuations. The American Economic Review (79), 14-31.
15. Brunnermeier M.K., Eisenbach T.M., and Sannikov Y., (2012). Macroeconomics with financial frictions: A survey. Working Paper 18102, National Bureau of Economic Research.
16. Brunnermeier, M. Clerc, L. & Scheicher, M., 2013. Assessing contagion risks in the CDS market. Financial Stability Review, Banque de France, issue 17, pages 123-134, April.
17. Caccioli, F., Catanach, TA., Farmer, JA., (2011). Heterogeneity, correlations and financial contagion. Arxiv preprint arXiv:1109.1213
18. Caccioli, F., Shrestha, M., Moore, C., Farmer, JD (2014). Stability analysis of financial contagion due to overlapping portfolios. Journal of Banking & Finance 46, 233-245.
19. Caccioli, F., Farmer, JD., Foti, N., Rockmore, D., (2015). Overlapping portfolios, contagion, and financial stability. Journal of Economic Dynamics and Control 51, 50-63.
20. Christiano L. and Ikeda D., (2011). Government Policy, Credit Markets and Economic Activity. NBER Working Papers 17142, National Bureau of Economic Research, Inc.
21. Ciola, E., (2019) Financial sector bargaining power, aggregate growth and systemic risk. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00270-5.
22. Clemente, G.P., Grassi, R. & Pederzoli, C. (2019). Networks and market-based measures of systemic risk: the European banking system in the aftermath of the financial crisis. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00247-4.
23. Colasante, A., García-Gallego, A., Georgantzis, N., Morone, A., (2019). Voluntary contributions in a system with uncertain returns: A case of systemic risk. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00276-z.

24. De Masi, G., Ricchiuti, G., (2019). From FDI network topology to macroeconomic instability. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00275-0.

25. Delli Gatti, D., Gallegati, M., Greenwald, B-C., Russo, A., Stiglitz, J-E., (2012). Mobility constraints, productivity trends, and extended crises, Journal of Economic Behavior & Organization, 83 (3), 375-393.

26. Fatone, L., Mariani, F., (2019). An assets-liabilities dynamical model of banking system and systemic risk governance. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00277-y.

27. Ferri P. and Minsky H.P., (1992). Market processes and thwarting systems. Structural Change and Economic Dynamics, 3(1):79-91.

28. Greenwald B.C. and Stiglitz J.E., (1993). Financial market imperfections and business cycles. Quarterly Journal of Economics, 108(1).

29. Grilli, R., Iori, G., Stamboglis, N., Tedeschi, G., (2017). Chapter 10 - A Networked Economy: A Survey on the Effect of Interaction in Credit Markets. Editor(s): Gallegati, M., Palestrini, A., Russo, A., Introduction to Agent-Based Economics, Academic Press, Pages 229-252, ISBN 9780128038345.

30. Grilli, R., Tedeschi, G., & Gallegati, M. (2014). Bank interlinkages and macroeconomic stability. International Review of Economics Finance, 34, 72-88.

31. Iori, G., Jafarey, S., & Padilla, F. G. (2006). Systemic risk on the interbank market. Journal of Economic Behavior Organization, 61(4), 525-542.

32. Kapar, B., Iori, G., Gabbi, Germano, G., (2019). Market Microstructure, Banks' Behaviour and Interbank Spreads. Evidence after the Crisis. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00248-3.

33. Kirman, A. (1991). Epidemics of opinion and speculative bubbles in financial markets. Money and financial markets, 3:54-368.

34. Kirman, A. (1993). Ants, rationality, and recruitment. The Quarterly Journal of Economics,137-156.

35. Lenzu, S., Tedeschi, G., (2012). Systemic risk on different interbank network topologies. Physica A: Statistical Mechanics and its Applications 391 (18), 4331-4341.

36. Lux, T., (2016). A model of the topology of the bank-firm credit network and its role as channel of contagion, Journal of Economic Dynamics and Control 66, 2016, 36-53.

37. Lux, T., and Montagna M., (2017). Contagion risk in the interbank market: A probabilistic approach to cope with incomplete structural information, Quantitative Finance 17 (1), 101-120.

38. Mancino, ME., Sanfelici, S., (2019). Identifying financial instability conditions using high frequency data. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00253-6.

39. Mazzarisi, P., Barucca, P., Lillo, F., & Tantari, D. (2020). A dynamic network model with persistent links and node-specific latent variables, with an application to the interbank market. European Journal of Operational Research, 281(1), 50-65.

40. Mazzocchetti, A., Lauretta, E., Raberto, M., Teglio, A., Cincotti, S., (2019). Systemic Financial Risk Indicators and Securitised Assets: an Agent-Based Framework. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00268-z.

41. Minsky H.P., (1964). Longer waves in financial relations: Financial factors in the more severe depressions. The American Economic Review, 54(3):324-335.

42. Rajan R.G., (1994). Why bank credit policies uctuate: A theory and some evidence. The Quarterly Journal of Economics, 109(2): 399-441.

43. Recchioni, MC., Tedeschi, G., Gallegati, M., (2015). A calibration procedure for analyzing stock price dynamics in an agent-based framework. Journal of Economic Dynamics and Control, (60),1-25.

44. Recchioni, MC., Tedeschi, G., (2017). From bond yield to macroeconomic instability: A parsimonious affine model. European Journal of Operational Research, 262 (3), Issue 3, 1116-1135.

45. Tedeschi, G., Mazloumian, A., Gallegati, M., & Helbing, D. (2012). Bankruptcy cascades in interbank markets. PloS one, 7(12), e52749.

46. Tedeschi, G., Recchioni, MC., Berardi, S, (2019). An approach to identifying micro behavior: How banks' strategies influence financial cycles. Journal of Economic Behavior & Organization, (162), 329-346.

47. Sakurai, Y., Kurosaki, T., (2019). A simulation analysis of systemic counterparty risk in over-the-counter derivatives markets. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00260-7.

48. Vidal-Tomás, D. and Alfarano, S., (2019). An agent-based early warning indicator for financial market instability. J Econ Interact Coord. https://doi.org/10.1007/s11403-019-00272-3